

# Adaptive Finite Element Methods

Peter Binev, **Wolfgang Dahmen**, Ronald DeVore

University of South Carolina / **RWTH Aachen**

# The Problem

$$-\Delta u = f$$

$$u = 0 \text{ on } \partial\Omega$$

$\Omega$  is a polygonal domain in  $\mathbb{R}^2$

1. Standard Finite Element Methods
2. Adaptive Finite Element Methods

IS THERE ANY ADVANTAGE TO ADAPTIVE METHODS

# Little Known

- 1998–2000: Convergence of certain AFEM

# Little Known

- 1998–2000: Convergence of certain AFEM
- I know of no AFEM ( $d \geq 2$ ) which is proven to outperform Standard Finite Element Methods for problems in  $\mathbb{R}^d$ ,  $d \geq 2$

# Goal

- More ambitious

# Goal

- More ambitious
- Give the 'mother' of all adaptive algorithms

# Galerkin Solutions

- $P$  a triangular partition of  $\Omega$

# Galerkin Solutions

- $P$  a triangular partition of  $\Omega$
- $S_P$  space of piecewise linear functions subordinate to  $P$  vanishing on  $\partial\Omega$



# Galerkin Solutions

- $P$  a triangular partition of  $\Omega$
- $\mathcal{S}_P$  space of piecewise linear functions subordinate to  $P$  vanishing on  $\partial\Omega$
- $u_P$  Galerkin solution

# Galerkin Solutions

- $P$  a triangular partition of  $\Omega$
- $\mathcal{S}_P$  space of piecewise linear functions subordinate to  $P$  vanishing on  $\partial\Omega$
- $u_P$  Galerkin solution
- $\|u - u_P\| = \inf_{S \in \mathcal{S}_P} \|u - S\|$

# Galerkin Solutions

- $P$  a triangular partition of  $\Omega$
- $\mathcal{S}_P$  space of piecewise linear functions subordinate to  $P$  vanishing on  $\partial\Omega$
- $u_P$  Galerkin solution
- $\|u - u_P\| = \inf_{S \in \mathcal{S}_P} \|u - S\|$
- $\|\cdot\|$  energy norm ( $H^1$ -norm)

# Typical Adaptive Algorithm: $P_k \rightarrow P_{k+1}$

1. Compute  $u_{P_k}$
2. Compute error indicators  $e(\Delta)$ ,  $\Delta \in P_k$ .  $e(\Delta)$  has two terms: (i) jumps in  $u_{P_k}$  across edges of  $\Delta$ , (ii) approximation of  $f$  by constants on  $\Delta$
3. Use local error indicators to mark cells  $\mathcal{M}_k$  in  $P_k$ : **bulk chasing**.
4. Refine cells in  $\mathcal{M}_k$  to obtain  $P'_k$
5. Remove hanging nodes: further markings  $\mathcal{M}'_k$
6. Refine cells in  $\mathcal{M}'_k$ :  $P'_k \rightarrow P_{k+1}$

# Rules of the game

- How to measure error?

# Rules of the game

- How to measure error?
- Energy norm:  $\|v\| = |v|_{H_0^1(\Omega)}$

# Rules of the game

- How to measure error?
- Energy norm:  $\|v\| = |v|_{H_0^1(\Omega)}$
- How to measure complexity?

# Rules of the game

- How to measure error?
- Energy norm:  $\|v\| = |v|_{H_0^1(\Omega)}$
- How to measure complexity?
- Number of computations



# Can we find "best" adaptive partitions

- Specify the methods more precisely

# Can we find "best" adaptive partitions

- Specify the methods more precisely
- Admissible partitions: minimum angle condition and no hanging nodes

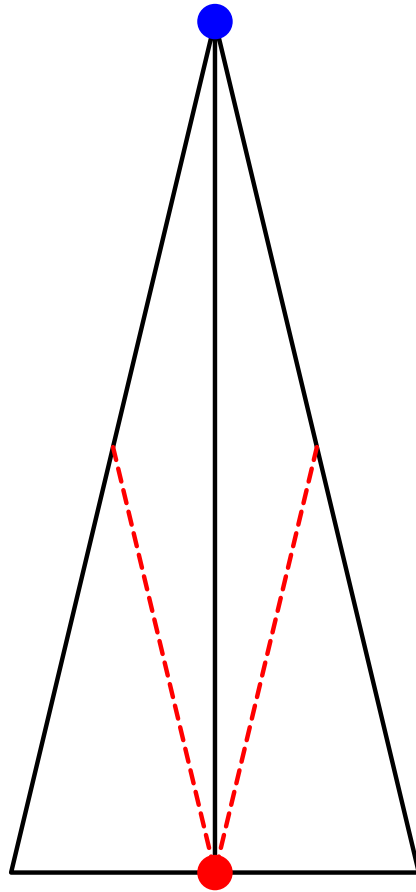
# Can we find "best" adaptive partitions

- Specify the methods more precisely
- Admissible partitions: minimum angle condition and no hanging nodes
- Can almost do that

# Can we find "best" adaptive partitions

- Specify the methods more precisely
- Admissible partitions: minimum angle condition and no hanging nodes
- Can almost do that
- Newest vertex bisection

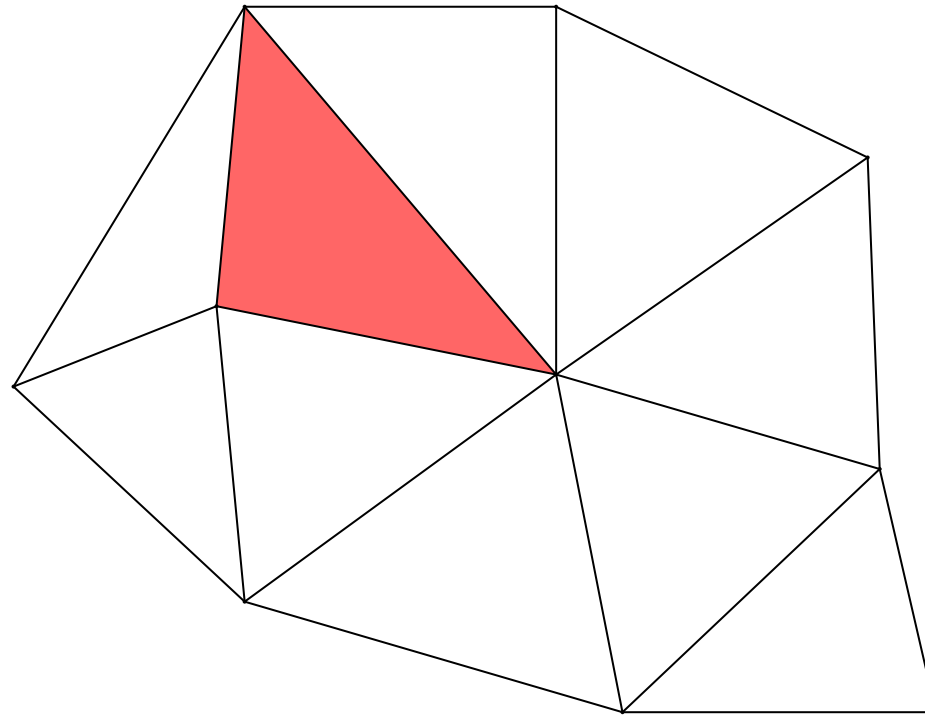
# Newest vertex bisection



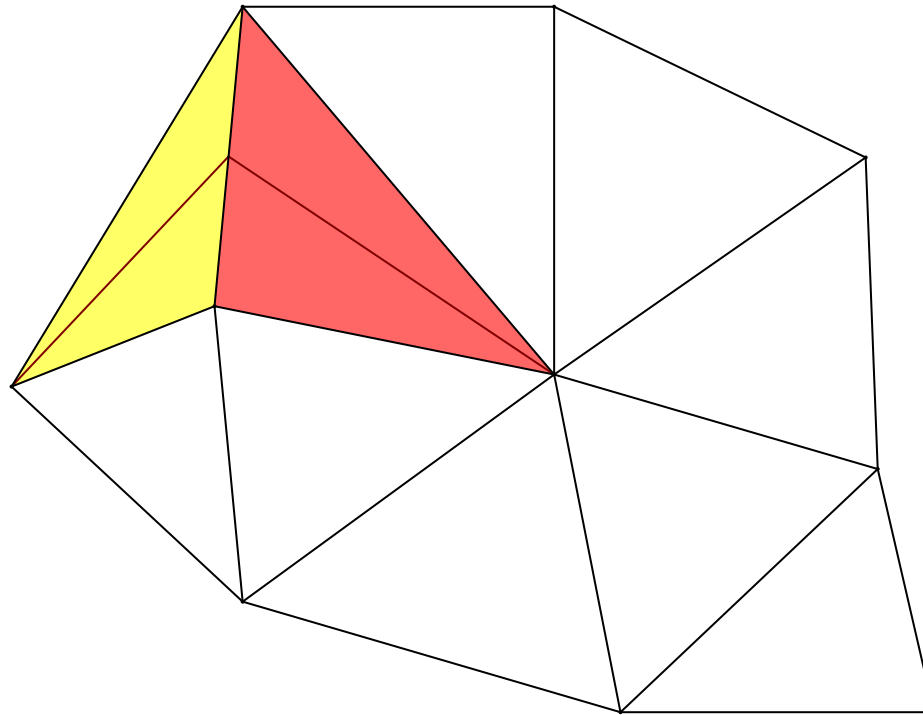
● newest vertex of big triangle

● newest vertex of new triangles

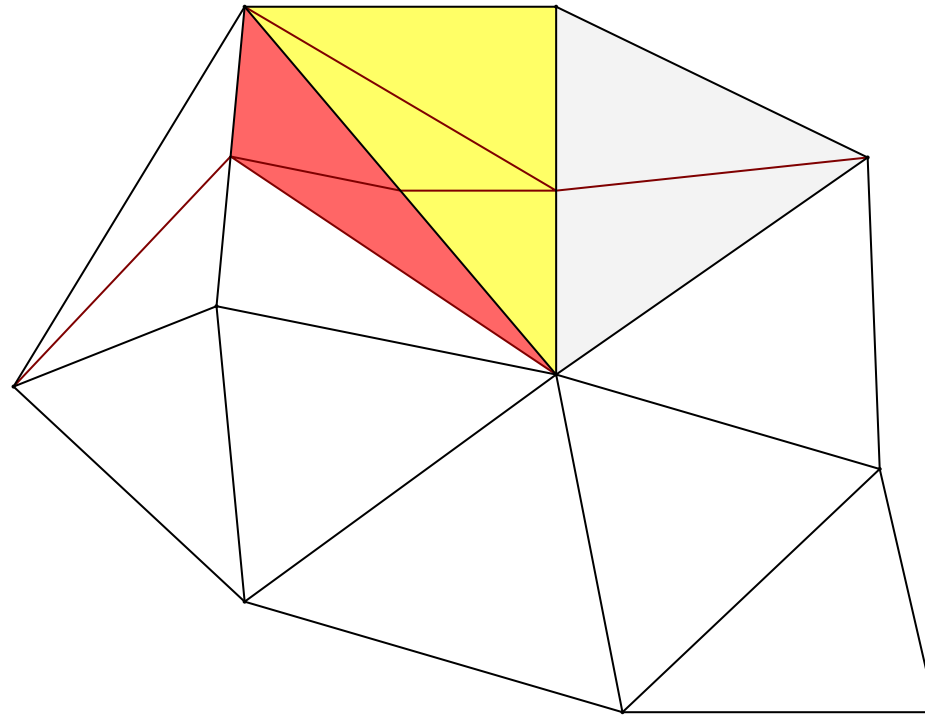
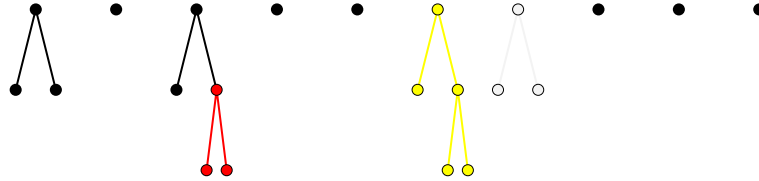
# Tree structure



# Refinement grows the tree

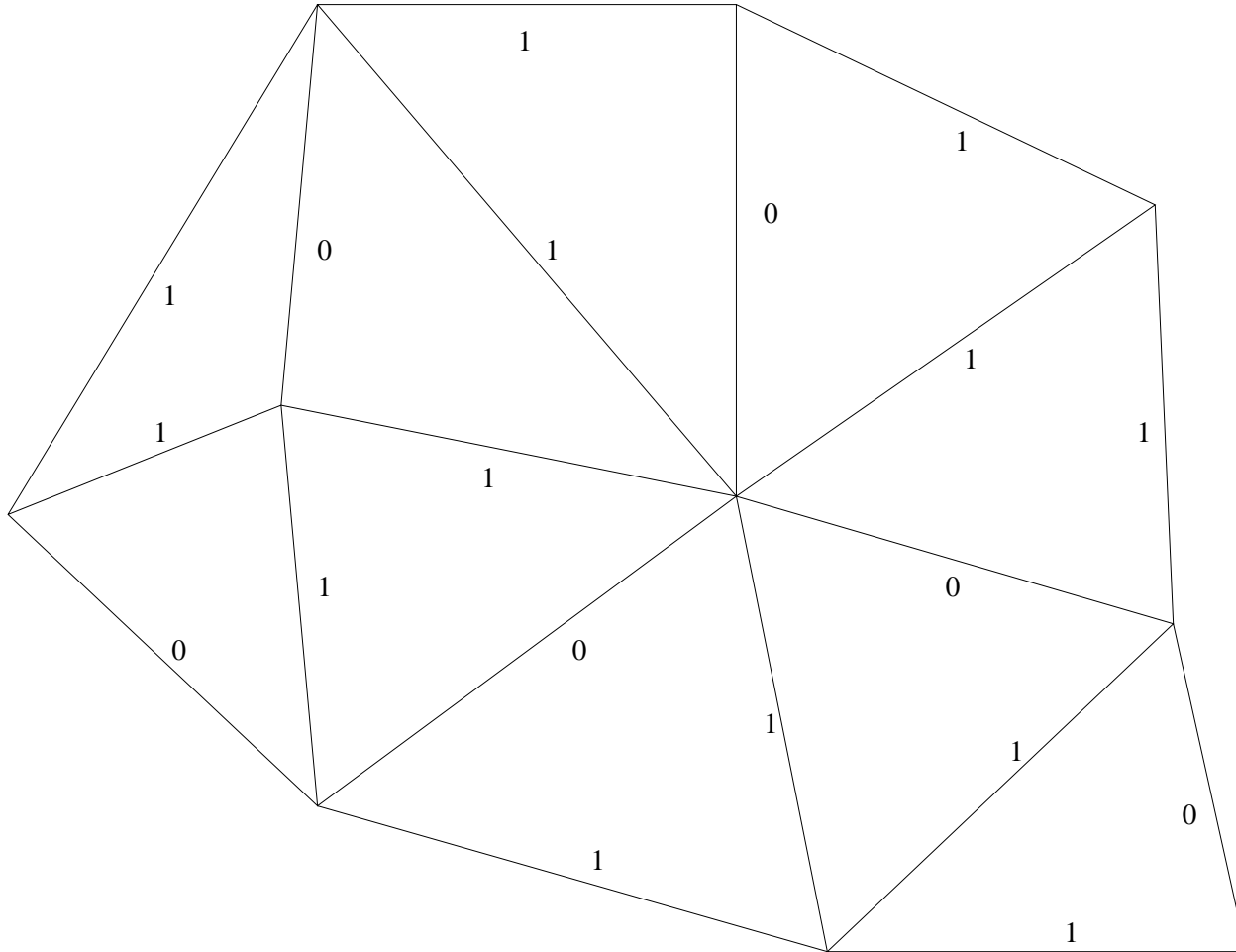


# Grow more

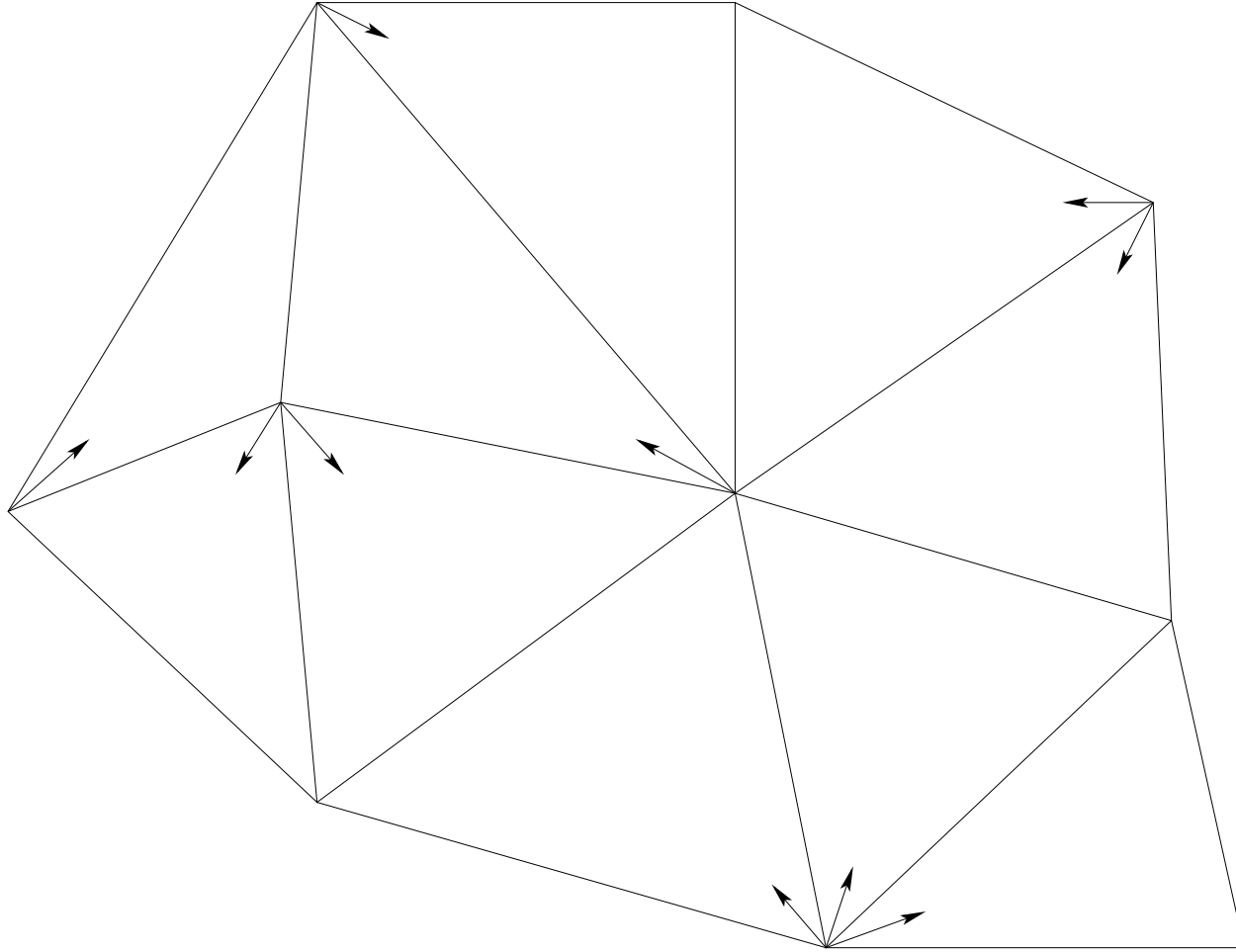




# Initial Labeling of edges



# Initial assignment of newest vertices



# Evaluate performance of an AFEM

- $N(P)$  number of subdivisions to create  $P$

# Evaluate performance of an AFEM

- $N(P)$  number of subdivisions to create  $P$
- $\mathcal{P}_n := \{P : N(P) = n\}$

$$\sigma_n(u) := \inf_{P \in \mathcal{P}_n} \|u - u_P\|$$

# Evaluate performance of an AFEM

- $N(P)$  number of subdivisions to create  $P$
- $\mathcal{P}_n := \{P : N(P) = n\}$

$$\sigma_n(u) := \inf_{P \in \mathcal{P}_n} \|u - u_P\|$$

- Could ask Numerical Alg. perform like  $\sigma_n(u)$

# Evaluate performance of an AFEM

- $N(P)$  number of subdivisions to create  $P$
- $\mathcal{P}_n := \{P : N(P) = n\}$

$$\sigma_n(u) := \inf_{P \in \mathcal{P}_n} \|u - u_P\|$$

- Could ask Numerical Alg. perform like  $\sigma_n(u)$
- For  $s > 0$ ,  $\mathcal{A}^s$  is the set of all  $u$  such that

$$\sigma_n(u) \leq Mn^{-s}, \quad n = 1, 2, \dots$$

# Evaluate performance of an AFEM

- $N(P)$  number of subdivisions to create  $P$
- $\mathcal{P}_n := \{P : N(P) = n\}$

$$\sigma_n(u) := \inf_{P \in \mathcal{P}_n} \|u - u_P\|$$

- Could ask Numerical Alg. perform like  $\sigma_n(u)$
- For  $s > 0$ ,  $\mathcal{A}^s$  is the set of all  $u$  such that

$$\sigma_n(u) \leq Mn^{-s}, \quad n = 1, 2, \dots$$

- Equivalent to  $\sigma_n(u) \leq \epsilon$  with  $n = C\epsilon^{-1/2}$

# Binev-Dahmen- DeVore Algorithm

For each  $\epsilon > 0$ , algorithm produces  $P_\epsilon$  such that

1.  $\|u - u_{P_\epsilon}\| \leq \epsilon$

2. If  $u \in \mathcal{A}^s$  then  $\#(P_\epsilon) \leq C_0 |u|_{\mathcal{A}^s} \epsilon^{-1/s}$

3. Number of computations used is  $\leq C_0 |u|_{\mathcal{A}^s} \epsilon^{-1/s}$

**COROLLARY:** The BDD AFEM beats Standard Finite Element Methods for a wide class of problems



# How to do Marking

## Bulk Chasing: Doerfler, Morin-Nochetto-Siebert

1. Uses error indicators  $e(\Delta)$
2. Choose smallest set  $\mathcal{M}_k$  such that

$$\sum_{\Delta \in \mathcal{M}_k} e(\Delta) \geq 1/2 \sum_{\Delta \in P_k} e(\Delta)$$

3. There exists  $0 < \lambda < 1$ : Given target accuracy  $\epsilon > 0$  and  $P_k$  which resolves  $f$  to accuracy  $\gamma\epsilon$ , then either

$$\|u - u_{P_{k+1}}\| < \epsilon$$

or

$$\|u - u_{P_{k+1}}\| \leq \lambda \|u - u_{P_k}\|$$

# Binev-Dahmen-DeVore Algorithm

$P_k \rightarrow P_{k+1}$ :

1.  $P_{k,0} := P_k$

2.  $P_{k,j-1} \rightarrow P_{k,j}$ ,  $j = 1, \dots, K$ :

$$\|u - u_{P_{k,j}}\| \leq \lambda \|u - u_{P_{k,j-1}}\|$$

3  $P_{k,K} \rightarrow P_{k+1}$  by **Coarsening**

# Two main results

- Refinements to remove hanging nodes do not inflate number of subdivisions severely

# Two main results

- Refinements to remove hanging nodes do not inflate number of subdivisions severely
- How to do **Coarsening**

# Control removal of hanging nodes

●  $P_0 \rightarrow P_1 \rightarrow \dots \rightarrow P_n$

# Control removal of hanging nodes

- $P_0 \rightarrow P_1 \rightarrow \dots \rightarrow P_n$
- $P_k \rightarrow P_{k+1}$  uses  $\mathcal{M}_k$  and  $\mathcal{M}'_k$

# Control removal of hanging nodes

- $P_0 \rightarrow P_1 \rightarrow \dots \rightarrow P_n$
- $P_k \rightarrow P_{k+1}$  uses  $\mathcal{M}_k$  and  $\mathcal{M}'_k$
- Theorem:

$$\#(P_n) \leq \#(P_0) + C(\#(\mathcal{M}_0) + \dots + \#(\mathcal{M}_{n-1}))$$

# Proof of Theorem

- Not simple induction: we do not have

$$\#\mathcal{M}'_k \leq C\#\mathcal{M}_k$$



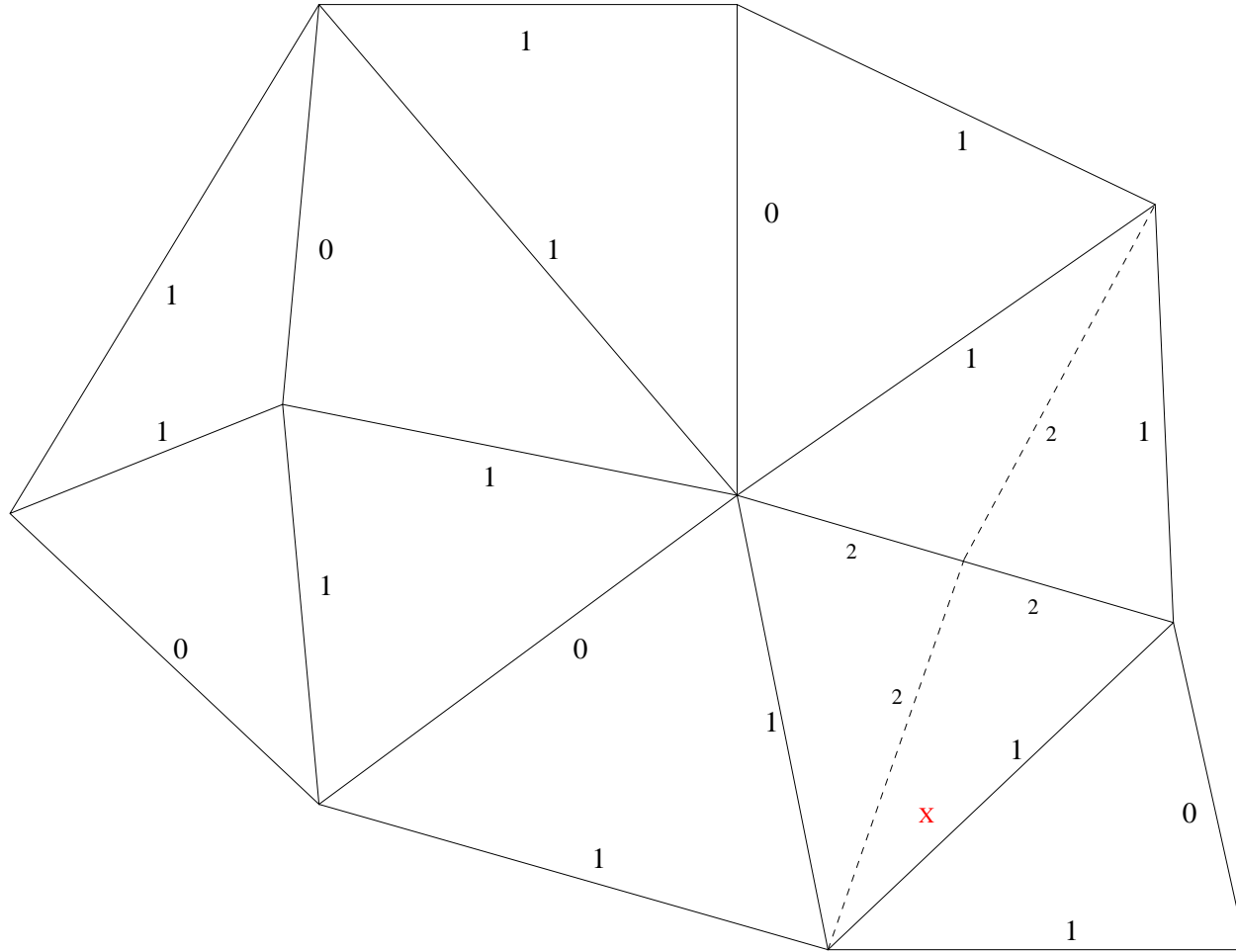
# Proof of Theorem

- Not simple induction: we do not have

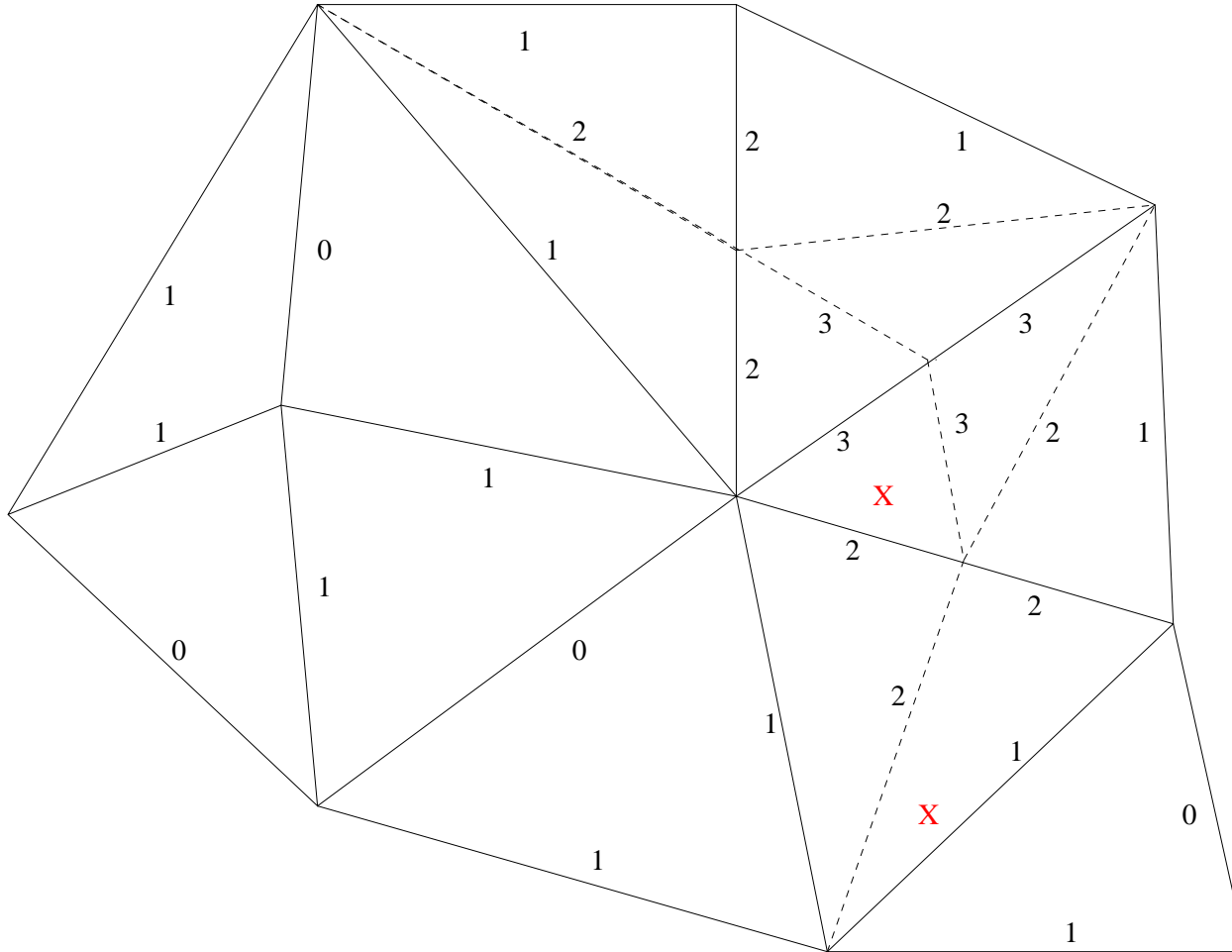
$$\#\mathcal{M}'_k \leq C\#\mathcal{M}_k$$

- Need to look at entire history of how  $\Delta \in P_n$  was created

# Many refinements



# Many refinements

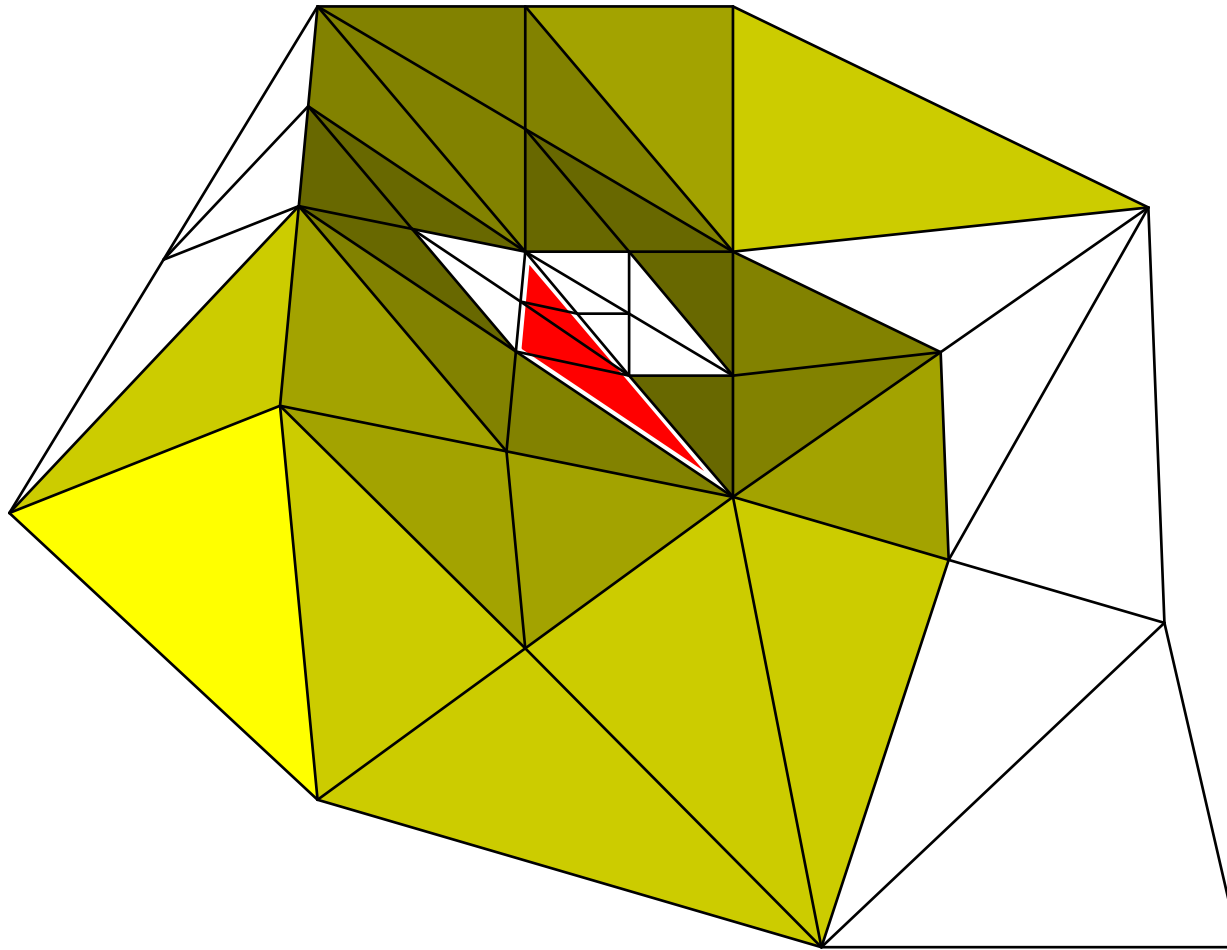


# Ideas:

1. Each cell in  $\mathcal{M} := \cup_{k=0}^{n-1} \mathcal{M}_k$  is given  $A$  dollars to spend
2.  $\Delta' \in P_n$  receives  $\lambda(\Delta, \Delta')$  dollars from a given  $\Delta \in \mathcal{M}$ .  
Here  $\lambda$  depends on the generations  $g(\Delta) = k$ ,  $g(\Delta') = j$  and the distance  $\text{dist}(\Delta, \Delta')$

$$\lambda(\Delta, \Delta') := \begin{cases} (j - k + 2)^{-2}, & \text{dist} \leq A2^{-k/2}; k \leq j + 1, \\ 0, & \text{otherwise.} \end{cases}$$

# Who's got the money?



# Ideas

3. Prove each  $\Delta' \in P_n$  receives at least  $B$  dollars from all of the  $\Delta \in \mathcal{M}$  combined.
4. The latter requires to look at how  $\Delta'$  is created, i.e. the set of markings responsible for the creation of  $\Delta'$ .

# Coarsening Algorithm

- $P_{k,K}$  and  $u_{P_{k,K}}$  known to us

# Coarsening Algorithm

- $P_{k,K}$  and  $u_{P_{k,K}}$  known to us
- $P_{k,K}$  may be too large



# Coarsening Algorithm

- $P_{k,K}$  and  $u_{P_{k,K}}$  known to us
- $P_{k,K}$  may be too large
- We want a sparse approximation to  $u_{P_{k,K}}$  by using a smaller set than  $P_{k,K}$

# Coarsening Algorithm

- $P_{k,K}$  and  $u_{P_{k,K}}$  known to us
- $P_{k,K}$  may be too large
- We want a sparse approximation to  $u_{P_{k,K}}$  by using a smaller set than  $P_{k,K}$
- Tree structure

# Coarsening Algorithm

- $P_{k,K}$  and  $u_{P_{k,K}}$  known to us
- $P_{k,K}$  may be too large
- We want a sparse approximation to  $u_{P_{k,K}}$  by using a smaller set than  $P_{k,K}$
- Tree structure
- master tree  $T_*$ : all cells  $\Delta$  that can be obtained by newest vertex bisection

# Tree approximation

- Error functional  $e(\Delta) \geq 0$  defined on nodes  $\Delta$  of master tree  $T_*$  -local error on cell

# Tree approximation

- Error functional  $e(\Delta) \geq 0$  defined on nodes  $\Delta$  of master tree  $T_*$  -local error on cell
- Assumptions on  $e$ : if  $T$  is a tree with single root  $\Delta$

$$\sum_{\Delta' \in \mathcal{L}(T)} e(\Delta') \leq C e(\Delta)$$

# Tree approximation

- Error functional  $e(\Delta) \geq 0$  defined on nodes  $\Delta$  of master tree  $T_*$  -local error on cell
- Assumptions on  $e$ : if  $T$  is a tree with single root  $\Delta$

$$\sum_{\Delta' \in \mathcal{L}(T)} e(\Delta') \leq C e(\Delta)$$

- Global error for tree  $T$ :  $\mathcal{L}(T)$  leaves of  $T$

$$E(T) := \sum_{\Delta \in \mathcal{L}(T)} e(\Delta)$$

# Near best tree approximation

- Best approximation

$$\sigma_n := \inf_{N(T)=n} E(T)$$

# Near best tree approximation

- Best approximation

$$\sigma_n := \inf_{N(T)=n} E(T)$$

- Near best tree  $T'$ :  $N(T') = n$

$$E(T') \leq C_1 \sigma_{c_1 n}$$



# Near best tree approximation

- Best approximation

$$\sigma_n := \inf_{N(T)=n} E(T)$$

- Near best tree  $T'$ :  $N(T') = n$

$$E(T') \leq C_1 \sigma_{c_1 n}$$

- Theorem (Binev-DeVore): Given  $\epsilon$ , can find a near best tree with  $Cn$  computations

# Ideas in proof

- Greedy strategy to subdivide those  $\Delta$  with largest  $e(\Delta)$  does not work

# Ideas in proof

- Greedy strategy to subdivide those  $\Delta$  with largest  $e(\Delta)$  does not work
- After each subdivision, redefine  $e$  (modified  $\tilde{e}$ )

# Ideas in proof

- Greedy strategy to subdivide those  $\Delta$  with largest  $e(\Delta)$  does not work
- After each subdivision, redefine  $e$  (modified  $\tilde{e}$ )
- Modification makes  $\tilde{e}(\Delta)$  smaller when previous subdivisions of the ancestor's of  $\Delta$  did not decrease error much

# Ideas in proof

- Greedy strategy to subdivide those  $\Delta$  with largest  $e(\Delta)$  does not work
- After each subdivision, redefine  $e$  (modified  $\tilde{e}$ )
- Modification makes  $\tilde{e}(\Delta)$  smaller when previous subdivisions of the ancestor's of  $\Delta$  did not decrease error much
- Greedy on  $\tilde{e}$